On Assessing the Positioning Accuracy of Google Tango in Challenging Indoor Environments

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***Abstract*—The major challenges for optical based tracking are the lighting condition, the similarity of the scene, and the position of the camera. This paper demonstrates that under such conditions, the positioning accuracy of Google's Tango platform may deteriorate from fine-grained centimetre level to metre level. The paper proposes a particle filter based approach to fuse the WiFi signal and the magnetic field, which are not considered by Tango, and outlines a dynamic positioning selection module to deliver seamless tracking service in these challenging environments.**

I. INTRODUCTION

In 2016, Google unveiled the world's first 3D augmented reality Tango-based consumer smartphone, which delivers low latency six degrees of freedom tracking and 3D reconstruction in one complete package[1]. This release was significant, as for the first time, the consumer was presented with a portable mobile device that has the potential of providing centimetre level indoor positioning, by mixing computer vision, inertial tracking, and machine learning.

Nevertheless, the major challenges posed for Tango are the lighting condition, the similarity of the scene, and the camera position, which are common hurdles for any optical based tracking system. This paper will illustrate that, under such conditions, Tango's fine-grained centimetre positioning accuracy may degrade to metre level, or worse, it may stop working completely (see Figure 1).

To tackle these challenges, this paper proposes a combination of two ubiquitous indoor elements - the WiFi signals and the magnetic field, that are not considered by Tango. They will be fused under a particle filter, which is governed by a dynamic switching system to select what tracking module to use under certain circumstance. More significantly, the addition of WiFi and magnetism does not require excessive effort in handling and maintenance, under our proposal. They will blend naturally into the Tango platform and may be applied in other existing Tango based systems. Ultimately, the paper aims to deliver a multi-modal system that combines vision, inertia, magnetism and WiFi signal in one complete platform.

[1] http://www3.lenovo.com/sg/en/smartphones/smartphone-phab-series/Lenovo-Phab-2-Pro/p/WMD00000220 - last accessed in 4/2017

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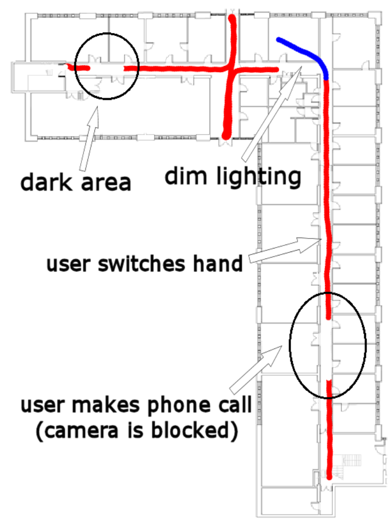


Fig. 1. The motivation for combining WiFi and magnetism to improve on Tango's positioning. Dark and dim lightings caused Tango to deviate heavily at corners. Clear front view is needed for Tango to operate.

Overall, the contributions of the paper are three-fold:

- We assess the positioning accuracy of the Tango mobile device in two realistic and challenging indoor environments, that are a large auditorium with wide space and symmetric structure, and an office building with dark corridors, which aim to exploit the weaknesses of optical-based tracking systems.
- We fuse the WiFi signal and the magnetic field by a Particle Filter to mitigate such challenges.
- We posit a novel positioning framework that dynamically moves between tracking modules to provide seamless indoor positioning service.

The remaining of the paper is organised into five sections. Section II overviews Tango's state-of-the-arts, emphasising on the limitations of such system. So that, Section III details our approach to tackle these challenges. Section IV then describes the test environments that exploit such weaknesses and the performance evaluation. Finally, Section V reviews the related work, and Section VI summaries the contributions and outlines further research.

II. An overview of the Tango platform

This section provides insight into the structure of Tango, emphasising on the challenges faced by such system.

A. Visual inertial odometry tracking

Visual inertial odometry (VIO) allows Tango to track its own movement and orientation in 3-dimensional space with six degrees of freedom. It achieves that by using an accelerometer to measure how fast the device is moving in which direction, a gyroscope to measure how much it is tilting, and a 160 degree wide angle fish-eye camera to calculate how far it is moving between frames. By combining inertial motions with visual input, Tango can work out its current whereabouts related to its starting position. This tracking process is performed up to 100 times a second in real-time, with the fish-eye camera provides 60 images per second.

B. Depth sensing

The challenge for VIO is that the device does not experience any depth perception of the surroundings. The camera is able to see the nearby objects, yet they appear as in a flat world. To mitigate this hindrance, Google offer three hardware-based resolutions. The first one is based on Structure Light which uses an infrared projector to send out an array of invisible infrared dots to illuminate the environment. Based on the size of the dots, observed by the camera, Tango knows how far away the object is (i.e. the smaller the dot, the nearer it is). The second option also relies on the infrared projector, however, it uses a dedicated camera to capture the reflected infrared beams, allowing it to measure the time-of-flight (ToF) taken to travel back and forth. The last option does not use infrared technology, but employs two horizontally adjacent cameras to emulate the human eyes. They allow the device to perceive the same scenery at slightly different perspectives to infer the depth with trigonometry. In summary, depth sensing equips Tango with the ability to recognise the shape of nearby objects, as well as the distance to them.

C. Area learning

While VIO and depth sensing allow Tango to achieve fine-grained short-term tracking, the long-term accuracy quickly deteriorates because of the accumulated sensors' error. This is a well-known challenge for inertial-based tracking. To mitigate this challenge, Google came up with a machine learning solution, called 'Area Learning'. Without learning, Tango has no memory of the environment. Hence, it can only trace its position back to the relative starting position $(0, 0, 0)$ of each session. With learning, Tango can re-position itself within a previously learned environment. By doing so, at the same time, it corrects any drifting errors from the sensors, and remains accurate over time.

To perform Area Learning, the user must let the Tango-based device experience the environment first hand, by walking through the tracking zone. Depending on the unique textures of the environment (i.e. furniture, interior layout), multiple walks from different cardinal directions may be needed for Tango to fully understand the building. At each position, Tango converts the visual information obtained via the camera and the depth sensors into searchable mathematical descriptions to be stored on the device. When needed, these entries can be quickly indexed to localise the device within the area (see Figure 2).

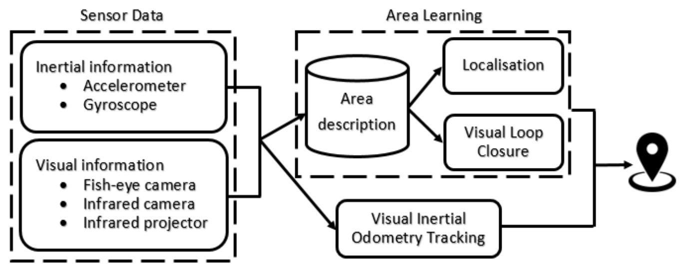


Fig. 2. The components and workflows of the Tango positioning platform.

D. Challenges

Equipped by the knowledge of the working internal system discussed above, this paper identifies three challenging settings that exploit the weaknesses of Tango.

Firstly, with every visual based system, the lighting remains a critical challenge. The fish-eye camera becomes under-exposed in low lighting and is over-exposed in bright scenes. Whereas, the dark surfaces absorb the infrared lights, which are also disoriented under sun lights. The low light condition is more common indoors, where most modern offices install motion sensor light for energy saving. These smart lights switch themselves off when no movements are detected, and do not react to brief movements. As such, the system may be left in the dark for some period of time.

Secondly, to enable tracking, Tango's camera must have a direct line of sight to the environment at the same time as the user does. This is a fair assumption for navigators, who should hold the device at chest level and at an angle to look at the screen for directions, which in turn, allows the back camera to observe the front scenery. Passive monitoring, however, renders the system useless because the device may be left in the pocket. Other practical scenarios include the user making a phone call while walking, for which the device is looking at one side of the user.

Thirdly, with Area Learning, Tango tries to memorise interesting features of the environments (e.g. objects with corners and edges). As such, blank indoor areas with no unique textures (e.g. large open space) may be harder to localise. Additionally, similar looking areas may confuse the system and put the user in the wrong position.

In summary, these scenarios may decrease the positioning accuracy, or worse, temporarily interrupting the Tango tracking service, as we will examine later on.

III. TOWARDS WIFI AND MAGNETIC BASED TRACKING FOR GOOGLE TANGO

We are now in a good position to explain our proposal to tackle the aforementioned challenges facing the Tango platform. We will progressively outline each working step and explore how our idea improves on it.

A. Off-line training

To enable localisation, prior knowledge of the tracking zone must be established in advance. For Tango, this process involves walking through the building at least once to allow Area Learning to create a mathematical model of the environment. With our approach, two additional WiFi and magnetism training databases are required. Some readers may immediately concern that these databases add burdens to collect and maintain, from which, other similar systems have suffered. However, two major distinctions of our approach are:

1) **Ease of generating the training databases.** The merit of our approach is that the magnetic field and the WiFi signals collection can be executed simultaneously along side the Tango learning process, with minimal effort from the surveyor. The key asset is since Tango provides the positioning co-ordinates automatically as it learns the environment, they can also be used to label the WiFi and magnetic samples.
2) **Ease of updating the training databases.** The major hassle of implementing a training database is that the changing environment requires occasional re-calibrations. Although obtaining fresh samples is straightforward, it is challenging to map them to the correct training index. With Area Learning, we can align the user's position to the trained ones. Hence, the old training samples can be updated with the latest ones.

For each snapshot, the device collects the WiFi fingerprint (i.e. the WiFi signal strength (RSS) from nearby WiFi Access Points) and the magnetic signature (i.e. the magnetic field strength along the 3-axes of the phone), and labels them with the Tango position. In the next sections, we will learn how to use these databases to handle the challenging scenarios.

B. Tracking with WiFi

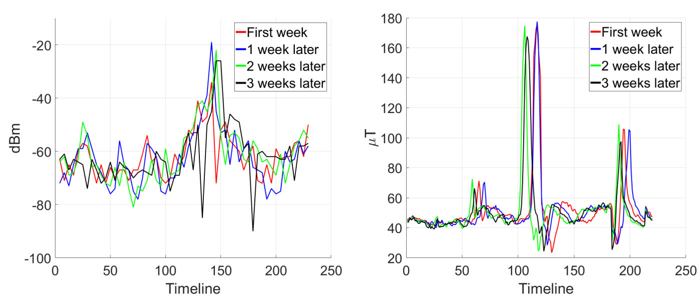
Given the WiFi training database generated from the last step, we match the real time WiFi sample recorded from the user to estimate his current position. This process is also known as WiFi fingerprinting, which has been the subject of extensive research in the past decade [1]. The main challenge of WiFi fingerprinting is the high volatility of the WiFi RSS, which aggravates the uncertainty of the matching process. It is well-accepted that the accuracy of WiFi fingerprinting is around 2-3 metres on average. As such, it is unintuitive to combine WiFi positioning with Tango that is capable of fine-grained centimetre accuracy. However, there are two scenarios that WiFi may improve on Tango.

1) **Tango does not work under poor lighting condition, or there is no front line-of-sight.** As Tango must see the front scenery to enable tracking, it does not work when the back camera is blocked (e.g. user puts the device at ear-level to make calls, or temporarily puts phone in pocket), or when the lighting is too dim. WiFi or magnetic field does not have this problem, and may substitute for the lack of vision in these scenarios.
2) **Wide space and plain looking areas with no unique features.** Tango's Area Learning distinguishes between positions by memorising the notable features of the scene. That means, similar looking areas or ones without any furniture may confuse Tango.

Our idea of utilising WiFi is allowing it to act as an anchor, for which the Tango based position is constrained within the estimated WiFi positioning circle. Additionally, WiFi positioning is useful when every other options fail (i.e. dark setting with non-coverage of magnetic database). In this paper, we employ the well-known Naïve Bayes classifier to perform WiFi fingerprinting [2].

C. Tracking with magnetism

In contrast to WiFi, indoor magnetism is known to be temporally stable (see Figure 3). However, the magnetic field strength (MFS) is not spatially unique, because it contributes just 3 measures for each position, which corresponds to the strength along each of the 3 axes of the phone. More challengingly, the 3D orientation of the phone varies the above measures. As such, they must be reduced into one total scalar magnitude (i.e. $\sqrt{(X^2 + Y^2 + Z^2)}$), which practically means we only have one magnetic field measure for every position. This is a huge challenge for magnetic field based positioning, because it is inevitable to observe the same magnetic magnitude in several positions in the tracking zone.



(a) Poor temporal uniqueness of the WiFi RSS of the same path over one month.

(b) Strong repeatability of the MFS for the same path. The slight spreading between trajectories was caused by small differences in walking speeds and shifting positions.

Fig. 3. Comparison of the WiFi RSS and the MFS surveyed on the same path, over one month. MFS' spatial uniqueness is salient.

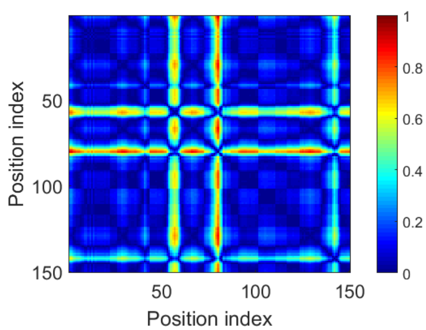
To tackle this challenge, we merge the magnetic field strength into a sequence to increase its dimension. Hence, each magnetic sequence does not just represent a single position, but a trajectory of all visited positions during this session. The rationale of our approach are:

1) **A trajectory is more distinctive than a position.** It is less likely to have two identical training magnetic paths.
2) **Most office corridors are long and narrow pathway.** As such, we assume there is one trajectory per corridor.
3) **Most users follow a straight walking direction.** In such constrained indoor space, we assume the user does not make random turns, except at the corners.

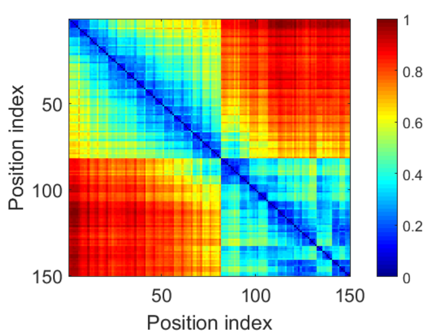
Essentially, with Tango providing the positioning label in real time, we can promptly identify which magnetic training trajectory to use and whereabouts on it the user starts walking, whereas other magnetic based systems must slowly build up the magnetic sequence until it is long enough to match. To compare two magnetic trajectories, we employ the well-known Dynamic Time Warping algorithm [3].

D. Fusion of WiFi and magnetism

Thus far, we have learned how to use WiFi and magnetism independently to estimate the user position. Nonetheless, it is logical to combine them for more accurate positioning given their complementary properties. That is, distant positions should observe different WiFi fingerprints, because of limited broadcasting range of the WiFi APs, but similar magnetic signature, thanks to its highly spatial similarity. In contrast, neighbour positions should perceive similar WiFi fingerprints, but different magnetic signature (see Figure 4).



(a) The Euclidean distance in the magnetic field space of neighbour positions can be large, whereas that of remote ones can be similar.



(b) The Euclidean distance in the WiFi signal space of neighbour positions are fairly similar, whereas that of remote ones are distinctive.

Fig. 4. The justification for combining WiFi and magnetism. The distance matrices for all pairs of continuous positions in our office test bed's floor.

Two most popular techniques to combine different sensors' reading in a time-series is the Kalman Filter (KF) and the Particle Filter (PF) [4]. We adopted the PF because of the non-Gaussian nature of the WiFi RSS, the magnetic field and the non-linearity of the user's movements. We avoid the hassle of implementing an Extended KF to satisfy these conditions.

The basic principle of a PF is recursively refining a set of positioning estimations (i.e. particles) based on the latest sensors' readings, on a per-step basis. The state of a particle includes its position (x, y), its heading direction $\vec{d}$, and a weight to represent the likelihood of being the true position. When the user moves, PF re-samples this set of particles to get rid of old ones, include new possible particles and update existing particles, according to the latest magnetic and WiFi signatures. Their detailed implementations are outlined below.

- **Particles initialisation.** With our approach, initial particles do not spread all over the map, but only circle around the previously known position suggested by Tango.
- **Particles weighing.** Each particle is assigned a weight that is the DTW distance between the training trajectory containing this particle and the actual observed trajectory.
- **Particles distribution.** As the user moves to a new position, the device records a new WiFi RSS, for which WiFi fingerprinting will recommend a new set of particles matching this sample. These newly introduced particles are essential to avoid the depletion problem, where we end up with only old unlikely particles. We propose a weight-based selection process, for which each new particle will be ranked against existing ones. As such, only those that are physically close in terms of the Euclidean distance are accepted (see Figure 5).

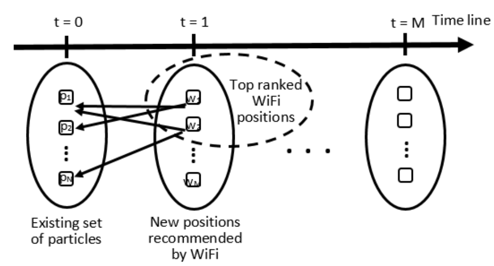


Fig. 5. The weight-based particle selection process. New particles are ranked against old ones, only the closest in terms of Euclidean distance are admitted.

- **Particles re-sampling.** After all particles are distributed, they will have their directions updated as follows, with $\vec{d_{gyro}}$ is the device's heading measured by the gyroscope.

$$\vec{d'} = \begin{cases} \vec{d_{gyro}}, & \text{for new particles} \\ \vec{d} + \vec{d_{gyro}}, & \text{for existing particles} \end{cases} \quad (1)$$

Simultaneously, we go through all current particles, and remove 50% particles with the lowest weights and those further away from the current estimated ones. Hence, under our proposal, an old particle will either die of low weight, or being out of range. This process is essential to avoid the number of particles going up exponentially as the user navigates.

E. A dynamic selection system

Having explained all core sensor based positioning modules (i.e. WiFi, magnetism, Tango) and understood their strengths and weaknesses, we are now in a good position to propose a system that decides what module to use to benefit certain scenario. The flow moves between three operating regimes (i.e. Tango positioning, WiFi positioning, and mixture of WiFi - Magnetism positioning) (see Figure 6).

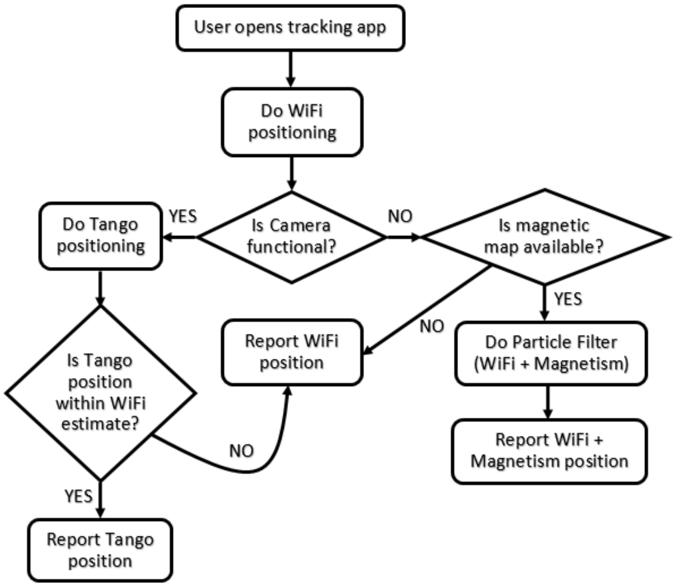


Fig. 6. The decision process of our system.

When the user opens the tracking app, the system performs WiFi fingerprinting to obtain a coarse positioning estimation. If the Tango position is not within this WiFi estimate, which indicates that Tango may confuse the current scenery with others in its training database, we ignore Tango position until it is within the WiFi circle. At any point during tracking that Tango's camera reports over- or under-exposure, we turn to the referenced magnetic trajectories, if available, to perform the PF of WiFi and magnetism, until Tango resumes functionality.

IV. Evaluation of performance

This section conducts the experiments to assess the performance of our proposal, and addresses the following research questions.

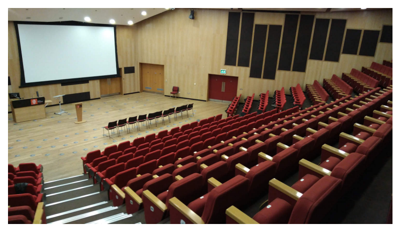
- **How much does Tango's positioning accuracy deteriorate in the experimented environments?** We hypothesise that Tango's performance may likely drop or even stop working all together.
- **To what extent WiFi and magnetism can support Tango in these scenarios?** Ideally, we expect to maintain a Tango-level accuracy with our proposal.

A. The test beds

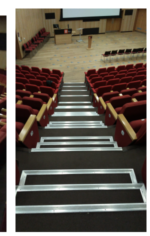
The first test bed is a three-storey building housing the Computer Science department of Royal Holloway University. The surveyed zone measures about 45 metres by 40 metres per floor, on three levels. The building is populated by motion based lights in the corridors, which will be exploited in our tests (see Figure 7a). The second test bed is a huge 500 seater auditorium of 900 square metres at the same university. The notable properties of this test bed are its symmetric structure, which portrays similar scenery from different positions' perspective, and its wide space with little furniture (see Figure 7c).

(a) The office test bed in normal lighting.

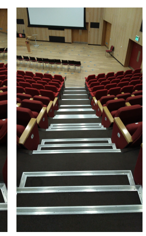
(b) The office test bed with part of the corridor in the dark.



(c) The auditorium test bed.



(d) Auditorium's left stair.

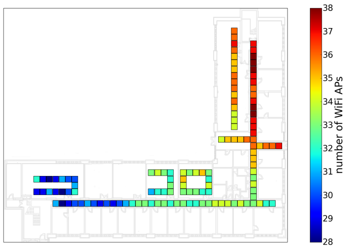


(e) Auditorium's right stair.

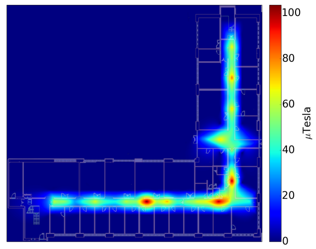
Fig. 7. The two test environments.

Training-wise, a surveyor walked through the building several times (i.e. twice in both directions for the office test bed, and in random directions for the auditorium test bed) to allow Tango to learn the area. The WiFi and magnetism training procedures were executed simultaneously along side the learning process, with the WiFi chipset collecting the WiFi RSS at 1.5 Hz and the magnetometer collecting the MFS at 5 Hz, and Tango providing the positioning label for all sensors' samples at 10 Hz. Note that we reduce Tango's sampling rate to 10 Hz to preserve battery, since this is a taxing process. Due to WiFi's low sampling rate, the surveyor walked consistently at a low speed to allow at least 1 WiFi sample every metre. In the tracking phase, the user may walk at various speeds, and the system would still be able to cope with, thanks to the dense coverage of the training databases and the algorithms we implemented.

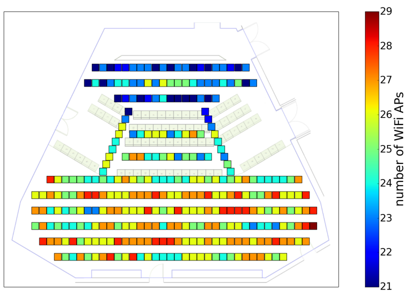
Testing-wise, we compiled an independent test set for each test bed. The challenge for doing so is that we have no other reference system that is more precise than Tango itself for ground-truth. Hence, we manually tape-marked several positions in each test bed. Through out the experiments, these known landmarks were visited multiple times, from different directions, using different routes. The evenly spaced office doors in the office test bed also helped as references to generate the test data. At each test position, the Euclidean distance of the estimated positioning co-ordinate and the true position was used to assess the performance accuracy. Since the aim of the paper is to maintain the performance of Tango in challenging environments, we do not have any test positions that are outside the training areas.



(a) WiFi coverage in one level of the office test bed.



(b) Magnetic coverage in one level of the office test bed exhibits high level of anomalies.



(c) WiFi coverage in the auditorium test bed.

Fig. 8. The training coverage of the two test environments.

All experimental periods were carried out during office-hours, with people walking in the building, and seen by the phone's camera. More details of the training and testing databases are summarised in Table I. The Tango device used in this paper is the Lenovo Phab 2 Pro smart phone, running Android Marshmallow. For evaluation purpose, we developed an app to collect the WiFi and magnetism.

TABLE I
SUMMARY OF THE TRAINING AND TESTING DATABASES FOR EACH TYPE OF SENSOR.

	Magnetometer	**WiFi**	**Tango**
Power consumption	Low	Average	High
Sampling rate	5 Hz	1.5 Hz	10 Hz
Training positions (office)	814	257	1667
Training positions (auditorium)	482	152	976
Test positions (office)	138	138	138
Test positions (auditorium)	45	45	45

B. Normal environment testing

Before committing into further challenging environments, we first test the positioning accuracy of Tango in normal, working environment, that is as close as possible to the one used to train the system. This result will act as a baseline for further testing. To our knowledge, since the release of the Tango mobile handset in December 2016, there has been no other work that assesses the performance of the device yet.

For this experiment, a tester walked through the above two test beds, with Tango providing the positioning estimations on the go. No WiFi or magnetism was used to improve Tango. For the office test bed, the result displays an impressively consistent accuracy of under 40 cm error, with the help of just Area Learning, whereas WiFi positioning managed a less impressive accuracy of about 2.5 m error. The performance gap, however, changes significantly for the auditorium test bed, where Tango struggled at about 3.5 m error, which was just slightly better than WiFi's. This result was down to the similarity of the scenes in this test bed, which will be examined later on (see Figure 9).

Overall, the results in this section suggested that under favourable conditions, Tango is capable of highly fine-grained centimetre accuracy.

C. Dark environment testing

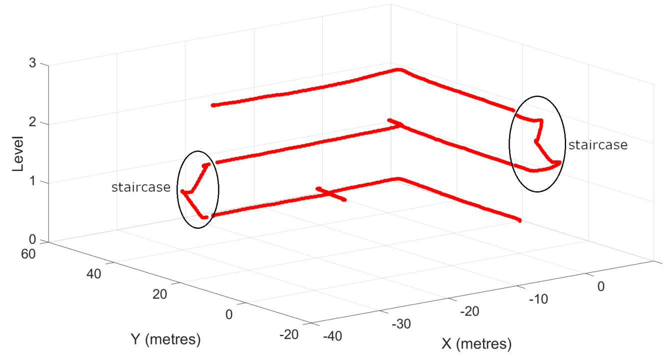
This test exploits the low lighting vulnerability of Tango with the motion based lights in the corridors of the office test bed. This experiment was performed in late evening, when the building was empty and all the lights were automatically off. As the tester walked through the corridors, the lights slowly turned themselves back on.

We noted two interesting observations. Firstly, the lights possess various sensitivities. So that, some of them did not react to brief or slow movements. Secondly, there was no co-ordination amongst them. Hence, each light is only aware of the direct space beneath itself. The resulting scenario was the user may be left in the dark or dim lighting in part of the corridor as he navigates through.

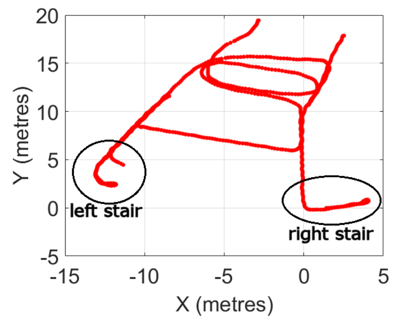
Nonetheless, the ultimate question is whether this condition has any impact on Tango's positioning. In complete darkness, Tango obviously stops working and our system can immediately engage to estimate the user position with WiFi and magnetism. In dim lighting, we noticed that Tango still operates although it is no longer certain of the surroundings. In straight corridor, VIO did an adequate job in maintaining Tango's trajectory. However, its path strongly deviates when the user turns corner (see Figure 10a). To tackle this challenge, we use the camera's exposure level to detect such situation (i.e. the camera is under-exposed), and allows our system to take over the positioning estimation. The result indicates a competitive performance using WiFi and magnetism, compared to Tango's (see Figure 10).

D. Similar scenery testing

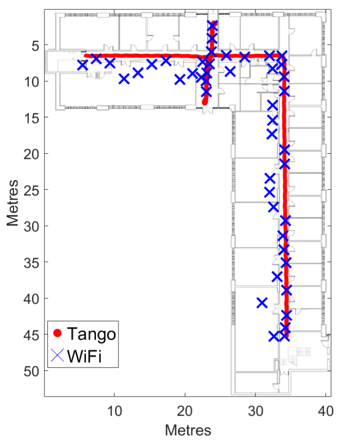
The tests in this section exploit the huge space and the symmetric structure of the auditorium test bed. In the first experiment, a tester walked around the large apron in a closed loop several times with only a podium and a few chairs in sight. Such conditions give away no unique elements for Tango to recognise. Unsurprisingly, Tango struggled to maintain the same path as he navigated, with the largest positioning error



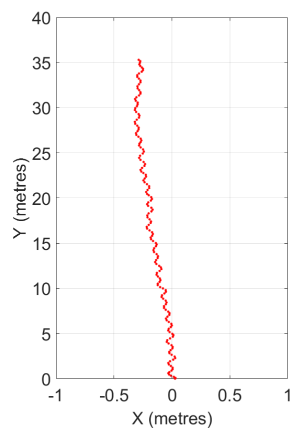
(a) 3D view of Tango navigation over 3 levels of the office test bed.



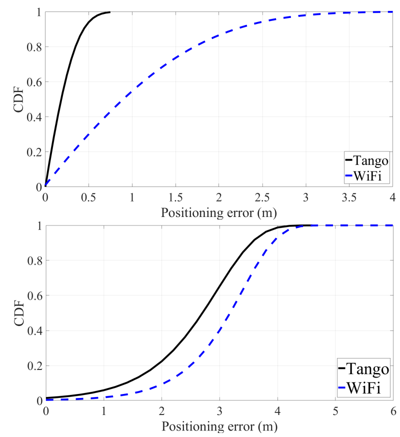
(b) 2D view of Tango navigation in the auditorium test bed.



(c) A comparison of Tango and WiFi positioning. WiFi positions frequently walked through walls and doors, whereas Tango positions closely follow the true trajectory.



(d) A close-up on the Tango's positions through a 35 m corridor as seen on the left, which were well within 40 cm error margin.



(e) Positioning accuracy with the test set for both test beds.

Fig. 9. The positioning accuracy of Tango in normal condition. Tango also achieves a much finer-grained positioning thanks to its higher sampling rate.

of about 2 metres, which was on the same level as WiFi's (see Figure 11a). The second experiment inspects the 2 stairs from both sides of the auditorium. A view from the top of these stairs offer almost the same scenery (see Figures 7d and 7e). Hence, Tango occasionally confused between the two, which results in position jumping from one stair to the other (see Figure 11b). With our proposal, we use the WiFi signal to constrain the positioning estimate. As such, the system would override the Tango's estimation in these cases, and uses WiFi fingerprinting as the replacement till Tango re-settles itself amongst the WiFi positioning estimation.

The positioning accuracy of Tango and our proposal for both test beds is summarised below (see Table II). Note that the maximum error does not account for the situations where Tango stops working.

TABLE II
POSITIONING ERRORS OF THE TWO TEST BEDS UNDER CHALLENGING CONDITIONS.

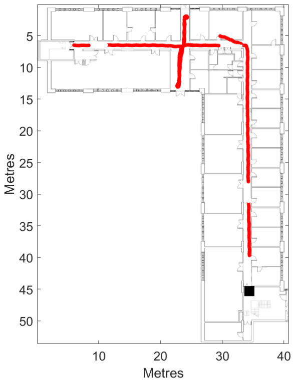
	Office		**Auditorium**	
	Tango	Our system	Tango	Our system
Mean (m)	0.34	0.27	6.53	2.43
Maximum (m)	0.57	1.36	17.24	3.19
Minimum (m)	0.02	0.02	0.05	1.38

V. Related Work

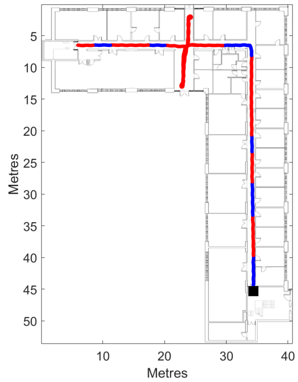
Since the essence of this paper is smart phone based optical tracking, we will only overview other related systems in the same area.

Azizyan et al. combine WiFi, magnetism, visual information, with other mobile sensors to construct a rich position's fingerprint [5]. However, the positioning result from independent sensors are simply intersected to obtain a final estimation. With our approach, the sensors' data are naturally fused under a PF for more accurate positioning. The magnetic field was also used to aid visual based information for other tracking systems [6], [7], [8]. Yet, it is mostly implemented along side accelerometer and gyroscope to track the user's motion.

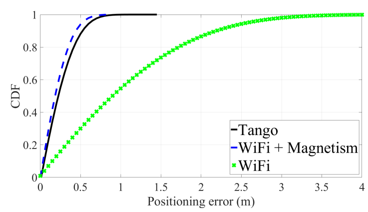
Alismail et al. attempted to mitigate the low lighting challenge of visual tracking by manipulating the image with binary feature descriptors [9]. Zheng et al. used the depth and infrared sensors incorporated on the Kinect to match images taken in low light with those in normal condition [10]. Although their



(a) Tango path contains several gaps caused by darkness where Tango completely stops working. This result displays the Tango positions in dim lighting, where VIO managed to follow the straight path till the corner, where it starts to deviate.



(b) The combination of WiFi and magnetism path is indicated by the blue line, which complements the red Tango path. This result demonstrates how often our system engages to support Tango.



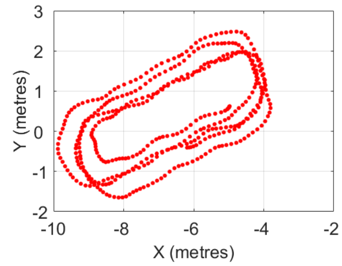
(c) Positioning accuracy of our approach using WiFi and magnetism clearly improved on Tango's. Note that this CDF does not reflect the position where Tango stops working, which happens often in this dark setting.

Fig. 10. The positioning accuracy of Tango and our system in dark environment. The black square indicates the starting position. All smart lights were off from the start.

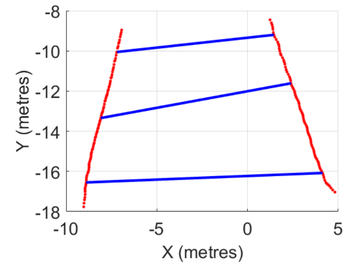
method was tested with Kinect, it is applicable for Tango based hardware. We took a different approach in this paper, by using non-optical wireless signals to compensate for the lack of vision in those scenarios.

VI. Conclusion and further work

We have presented a novel approach to mitigate the challenges facing the Tango tracking platform using the WiFi signals and the magnetic field strength. Our work was one of the first to assess the positioning accuracy of Tango in the small form factor of a mobile device. We exploit the positioning co-ordinates generated by Tango and area learning as references to label the WiFi and magnetic samples in normal conditions. These training databases will later be used to complement Tango's positions in challenging environments, where the device's camera is under-exposed in dark lighting, and when area learning mistakenly identifies the wrong location due to the lack of unique textures of the surroundings. We have assessed our approach in an office building with motion based lights, and in a huge auditorium with symmetric structure, where Tango struggled to deliver the positioning



(a) A closed loop walk in a clear area with little unique visual. Tango struggled to maintain the same trajectory.



(b) The two red lines are the two walks down the stairs. The blue line connects the positions on the walks where Tango confuses due to similar views.

Fig. 11. The positioning accuracy of Tango in wide, clear space, without much textures in the surroundings, and in areas with similar views.

service. Under our proposal, the system managed to maintain a similar Tango-level accuracy.

In the past few years, indoor localisation has transitioned from single specific sensor based technology to a more general multi-modal platform, thanks to the proliferate of the smart phone. This is an exciting but challenging approach, because although we have much more information at our disposal, how to combine all those sensors' data efficiently is still an open-ended question. Our work will continue to explore more effective means to fuse the magnetic field and WiFi with the vision based platform provided by Tango.

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